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Sales Seasonality Premium in Europe

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Abstract

Sorting stocks based on sales seasonality has yielded statistically significant premium in the United States over the period of 1972-2017 (Grullon, Kaba and Núñez-Torres, 2020). According to my results, the same effect is also present in Europe over the period of January 2003 - June 2021 as shorting stocks at their high season and buying stocks at their low season has yielded an annual alpha of 9.36%, independently of other known asset pricing factors and seasonalities. I examine multiple explanations behind the phenomena, namely investments, changes in capital structure and investor attention.

Key words: Sales seasonality, asset pricing, return predictability, market efficiency

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1. Introduction

For most firms, fluctuations in sales between quarters caused by market dynamics are easy to foresee and estimate in advance. For example, a Finnish energy company, Fortum, generates most of its revenues during winter when the electricity consumption is higher (Fortum, 2021).This paper pursues to answer to the question whether these changes in fundamentals can be used to predict future stock returns.

In a recent study by Grullon, Kaba and Núñez-Torres (2020) the authors find that "seasonal patterns in fundamentals can generate time variation in stock returns", meaning that, in the United States, by shorting high season companies and buying low season companies, an investor would have acquired a statistically significant annual alpha of 8.4% after controlling for Fama-French five-factors (Fama and French, 2015). My paper replicates this study with European data to find out if the same effect applies here.

Indeed, I find similar results than Grullon, Kaba and Núñez-Torres. In Europe, the same strategy of going long on stocks during their low-season and short on high-season has generated an annual alpha of 9.36% with a t-statistic of 2.22 after controlling for Fama-French five-factors. This premium arises mostly from the short leg of the portfolio: in value-weighted returns, low season portfolio has yielded an annual alpha of 0.84% and high season portfolio an annual alpha of -8.52%. This is opposite to Grullon et al. (2020) who find that, in their sample, sales seasonality premium originated mainly from the long leg.

Consistent with Grullon et al. (2020), the sales seasonality premium also increases with the size of a firm and is higher with the companies facing more variability in their quarterly sales within year. These findings suggest, respectively, that small firm effect is not driving the sales seasonality premium and that the premium is originating from the variability of companies' own fundamentals. Moreover, after sorting for variability in quarterly sales, my results are closer to Grullon et al. (2020) as a major part of the sales seasonality premium is originating from the long leg of the portfolio with the companies that have higher variability in their sales.

I also find that the sales seasonality premium is independent of other commonly used factors. A sales seasonality factor formed by the Fama-French convention has no significant correlation with the Fama-French five-factors, momentum or factor of seasonality presented by Heston and Sadka (2008), which is based on same month past abnormal returns. However, opposite to Grullon et. al (2020), I find that the sales seasonality premium in Europe has been performing worse – measured by Sharpe ratio – than many other factors.

At first glance, the sales seasonality premium seems to violate the efficient market hypothesis, but in this study, I test multiple rational explanations suggested by Grullon et al. (2020) to determine whether such assumption is correct. The first possible explanation that I test is the real option theory which states that, if firms invest more during high season, their expected return should be lower during these seasons. As stated by Grullon et al. (2020), "growth opportunities have embedded real options, creating levered positions on the underlying assets.". Therefore, when firms invest – considering also that the firms favour investments with less systematic risk while keeping all else equal – they actually reduce their systematic risks and therefore also expected return (Berk, Green and Naik, 1999). To support the real option theory, I find similarly to Grullon et al. (2020) that investments are higher during and prior to high seasons.

Systematic changes in leverage could also explain the variation of returns as debt increases exposure to systematic risks (Hamada, 1972). To support this theory, I should find a negative correlation between the sales seasonality and change in debt but, based on my results, the correlation is not statistically significant.

Variation in investor attention could also explain the sales seasonality premium. Merton (1987) predicts that, when stocks receive less attention, the expected returns thereof should be higher. Therefore, if there is systematically less attention to companies at their low season, their returns should be higher. Overall, I did not find both strong and consistent support for this theory: I find that companies face systematically lower turnover during their low-season, which supports the investor attention theory, but other variables used to estimate the investor attention level – namely illiquidity and changes in institutional ownership – are statistically insignificant.

I also find that dispersions in analyst estimates are systematically higher during low season, meaning based on theory by Dumas, Kurshev and Uppal (2009), that investors demand compensation for overconfident investors who bring more volatility into stock. Alternative theories imply that investors demand premia due to the risk of trading against investors whose vision has more influence on stock prices (David, 2008) or that, when combining short-selling constraints and higher dispersion in expectations, a stock could become overvalued as its valuation reflects only optimistic investors' beliefs (Miller, 1997).

I further test the investor attention theory with post-earnings announcement drift[1]. The logic behind this is that, if low season stocks are temporarily neglected, they should also incorporate new information slower. Grullon et. al (2020) find that low season stocks systematically react slower to positive news while high season stocks incorporate new information fastest. I did not find any evidence strongly consistent with this theory: in my data, the high season stocks actually incorporated new positive information more slowly, i.e., the post earnings announcement drift is the strongest among high season stocks. Conversely, low season stocks incorporate bad news more slowly than high season stocks, but low season stocks did not have the strongest post-earnings announcement drift.

A replicating study of sales seasonality premium on Chinese data suggests that the effect does not exist in the Chinese market (Huang, Tan and Zhao, 2020). As the authors point out, the Chinese market is dominated by retail investors and, thus, if the sales seasonality premium is originating from behavioural biases, it should be stronger in China. However, Chinese accounting practises have – at least in the past had – number of issues which makes local data less reliable compared to Western one. (Wang and Wu, 2011). Therefore, even though Huang et al. (2020) did not find any sales seasonality premium in China, behavioural biases can still be causing the premium.

The rest of this paper proceeds in the following manner: Section 2 describes data and methodology, Section 3 provides the main results and robustness checks, Section 4 investigate potential reasons behind the sales seasonality premium, Section 5 concludes the study, and Appendix provides more profound information about the variables used and includes tables concerning certain robustness checks.

[1] See for example Hirshleifer, Lim and Teoh (2009).

2. Data and methodology

My data, collected from Eikon, Datastream and I/B/E/S, comprises all the primary listed and delisted nonfinancial companies from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon and, in respect of companies that have multiple stock series, I only include the more traded series as otherwise some firms would have stronger effect on portfolio return than in reality. I combine monthly market data to quarterly and annual fundamental data. All yearly variables are formed at the end of June in year t with data from year t - 1 and used until June in year t + 1. In total, there are 7,892 firms from January 2000 to June 2021 in my data set. As due to missing values, which are focused on earlier years, the average amount of firm observations per month is 954 [2] and, in total, I have 214,650 firm-month observations. To tackle errors in Datastream data, I remove any returns which are over 300% and are reversed within one month, as suggested by Ince and Porter (2006).

My data set is smaller than Grullon et al.'s as they have data from 1970-2017 with a total of 14,008 firms and 1,509,794 firm-month observations. Because their data is from a longer period, it might capture better the performance of the sales seasonality strategy in different market environments. However, my data set also captures a long period of bull market and three market crashes caused by the financial crisis, euro crisis and, more recently, the Covid-19, so different market environments are represented in my data as well.

I measure sales seasonality by SEA_{qt} variable which is sales in quarter q of year t scaled by the annual sales in year t. I remove any observations with negative quarterly sales or nonpositive annual sales. I also require firms to have non-missing sales data for all four quarters during a year. When the sum of quarterly sales does not equal total sales from the annual data, I include only such firm-year observations in which the sum of quarterly sales is between 95% and 105% of the total annual sales.

To predict future sales seasonality in year t and to reduce effects of outliers or one-time shocks, I calculate variable $AVGSEA_{qt}$, which is average of SEA_{qt} in years t-3 and t-2. This ensures that the information is available to investors when the portfolio is formed. Companies with steady sales during the year should experience $AVGSEA_{qt}$ to be around 25% during all quarters and the companies with

[2] The median for the same period is 1,072 firms.

fluctuation in sales within quarters should face $AVGSEA_{qt}$ to be over 25% during their high seasons and under 25 % during their low seasons.

The main advantage of using sales to measure seasonality is that it has a lower change of being affected by changes in capital structure or nonrecurring items and it does not cause bias due to negative values (Grullon, Kaba and Núñez-Torres, 2020). I also test my main findings using cost of goods sold (COGS), selling, general and administrative expenses (SGAE), operational cashflows (OCF), and net profit (NP) as a basis for the sales seasonality. However, my main findings turn out be insignificant using these alternative measures. This can be due to – in addition to all other previously mentioned issues – smaller amount of data available with these variables: average amount of firm observation per month is 740, 806, 691, and 605, respectively, when calculating seasonality with these variables.

To measure persistence of sales seasonality, I calculate the average portion of firms from high and low-season portfolio that either remain in their original portfolio or travel to the opposite decile in t + 1 and t + 2. Table 1 Panel A below presents the persistency of firms sorted by average sales seasonality. As can be seen, about half of the firms in the highest or the lowest decile remains in the same decile within one year. Considering a two-year period, around one third of the firms remain in the same decile. Similarly, about 2.5% (5.5%) of the firms in high or low decile wander to opposite portfolio within one-year (two-year) time. In their study, Grullon, Kaba and Núñez-Torres (2020) have higher numbers of persistency: specifically, around 66% (50%) of the firms in their low or high-season also remain in the same decile within one-year (two-year) time.

The fact that firms also face temporary idiosyncratic shocks which affect the sales might have influence on the result discussed above. For this reason, I calculate variable SEAVAR which equals absolute change in SEA_{qt} in year t - 3 and t – 2. Then, I divide my sample in half in each quarter based on SEAVAR after which I sort both samples based on their $AVGSEA_{qt}$. The results are shown in Table 1 Panel B and C. Consistent with Grullon et al. (2020), I find that firms below the SEAVAR median remain more often in their respective portfolio: approximately 64% after one year and approximately 45% after two years. On the other hand, approximately 38% of the firms above the SEAVAR median remain in their respective portfolio after one year and approximately 19% after two years.

Table 1: Persistency of sales seasonality

This table shows the part of the firms in high and low sales season (SEA_{qt}) portfolios at time t that either remain in the same seasonality portfolio or travel to the other end at time t + 1 or t + 2. SEA_{qt} is equal to quarterly sales in quarter q year t scaled by annual sales in year t. To reduce the effect of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$, which is the average of SEAqt in years t-3 and t-2. SEAVAR is equal to the absolute change between SEA_{qt} in year t - 3 and t - 2. Panel A shows the entire sample, Panel B uses a subsample of firms below the SEAVAR median and then sorts on AVGSEA deciles, while Panel C uses a subsample of firms above the SEAVAR median and then sorts on the AVGSEA deciles. The data consist of all primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have a RIC-code linked in Eikon.

Panel A: Entire sample

		T + 1				T + 2	
		Low-season portfolio	High-season portfolio			Low-season portfolio	High-season portfolio
T	Low-season portfolio	51,40 %	2,52 %	T	Low-season portfolio	32,67 %	5,45 %
	High-season portfolio	2,83 %	56,36 %		High-season portfolio	5,76 %	36,57 %

Panel B: Below-median SEAVAR

		T + 1				T + 2	
		Low-season portfolio	High-season portfolio			Low-season portfolio	High-season portfolio
T	Low-season portfolio	63,66 %	0,00 %	T	Low-season portfolio	45,25 %	0,63 %
	High-season portfolio	0,00 %	65,41 %		High-season portfolio	0,59 %	46,03 %

Panel C: Above-median SEAVAR

		T + 1				T + 2	
		Low-season portfolio	High-season portfolio			Low-season portfolio	High-season portfolio
T	Low-season portfolio	37,59 %	2,80 %	T	Low-season portfolio	19,34 %	6,91 %
	High-season portfolio	3,46 %	38,26 %		High-season portfolio	7,25 %	19,60 %

3. Sales seasonality premium

3.1 Main results

To see if the sales seasonality has predicting power for future stock returns, I allocate stocks into deciles based on their $AVGSEA_{qt}$ in year t. The portfolios are rebalanced at the beginning of each month. I use three asset pricing models to control for different factors: CAPM, Fama and French three-factor model as well as Fama and French five-factor model.

Alphas and factor loadings from trading strategy for both equal- and value-weighted returns are shown in Table 2 below. Panel A shows values for equal weighted portfolios. The CAPM lowest decile has an average annual alpha of 3.48% (t-statistics = 1.09) and the highest decile has an average annual alpha of 1.56% (t-statistics = 0.58). The long-short portfolio has average annual CAPM alpha of 1.8% which also is not statistically significant (t-statistics = 0.98). After controlling for the Fama-French three-factor, the low-season portfolio has an average annual alpha of 1.8 (t-statistics = 0.60) and the high-season portfolio has an annual average alpha of -0.12% (t-statistics = -0.05). The long-short portfolio has an average annual Fama-French three-factor alpha of 1.92% which is statistically insignificant (t-statistics = 0.98). When controlling for the Fama-French five-factor, the low-season has an annual average alpha of 3.72% (t-statistics = 1.18) and the highest decile has an average annual alpha of 1.08% (t-statistics = 0.39). The long-short portfolio has an average annual Fama-French five-factor alpha of 2.64% which is statistically insignificant (t-statistics = 1.30). Opposite to Grullon et al. (2020), my long-short portfolios have insignificant alphas which originates from both higher alphas on short-portfolios and lower alphas on long-portfolios than in their sample. It is also notable that every equal-weighted portfolio has statistically significant positive coefficient for SMB suggesting that the returns of equal-weighted portfolios are in varying degree due to small-firm risk premia. Graph 1 below shows cumulative returns for both equal-weighted and value-weighted portfolios from January 2003 to June 2021. As can be seen from the first graph showing equal weighted returns, the low-season portfolio has yielded the highest cumulative returns from January 2003 to May 2021, but the returns are achieved with larger exposure to small firms which are known for their small firm risk premia[3]. A similar effect is also present in the returns of high-season equally weighted portfolio.

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[3] See for example Fama and French (1992).

Table 2 Panel B shows factor loadings of value-weighted portfolios. The CAPM low-season portfolio has an average annual alpha of 2.64% (t-statistics = 0.77) and the high-season portfolio has an average annual alpha of -6.84% (t-statistics = -2.24). The long-short portfolio has an average annual alpha 9.48% (t-statistics = 2,41). When controlling for the Fama-French three-factor, the low-season portfolio has an average annual alpha of 2.52% (t-statistics = 0,71) and the high-season portfolio has an average annual alpha of -6.84% (t-statistics = -2,22). The long-short portfolio has an average annual alpha of 9.36% (t-statistics = 2,34). When controlling for the Fama-French five-factor, the low-season portfolio has an average annual alpha of 0.84% (t-statistics = 0,23) and the high-season portfolio has an average annual alpha of -8.52% (t-statistics = -2,62). The long-short portfolio has an average annual alpha of 9.36% (t-statistics = 2,22). As can been seen from the value-weighted cumulative returns on Graph 1, the low minus high strategy has been performing well after the financial crisis in 2007 and losing to market index in cumulative returns only after the Covid-19 stock market crash. It is also worth noting that, during Covid-19 crash, the stocks in the short leg of the portfolio fell much less than the long leg, resulting that the hedge from it was not sufficient to cover the losses of the long-portfolio. This same effect occurred also in late 2015. These findings suggest that the sales seasonality strategy could include tail risk due to co-movement.

The above described finding are consistent with Grullon, Kaba and Núñez-Torres (2020) who show that sales seasonality premium is stronger with value-weighted portfolios. However, in their study, they find that the sales seasonality premium is originating mostly from the long leg of the portfolio while, in my sample, the premium is originating mainly from the short leg. This can be partially explained by the factor loadings of the short leg: it has statistically significant positive exposure to HML, which has yielded negative profit in Europe over period of January 2003 - June 2021 based on calculations shown later in this section.

As mentioned in the data-section, I also test the seasonality premium by calculating seasonality with cost of goods sold (COGS), selling, general and administrative expenses (SGAE), operational cashflows (OCF), and net profit (NP) as a basis for the sales seasonality. The problem with the variables that allow negative values is that a same firm might end up in low or high-season portfolio several times during a year.

My main findings turn out be insignificant using these alternative measures, which can be due to issues mentioned in the data-section. I report the factor loadings for the value-weighted portfolios of these alternative measures in Table A1 in Appendix. Grullon et al. (2020) finds that the cost of goods sold and operating cashflows provide similar results as sales and that using net profits, selling, and general and administrative expenses provide result in smaller magnitude but that they also are still statistically significant. This collision between my and Grullon's et al. results is casting a doubt on the sales seasonality premium's existence in Europe. However, my other robustness checks and economic test are, in most parts, in line with the findings of Grullon et al.

Table 2: Predictive power of sales seasonality

This table shows the monthly factor loadings of the portfolios sorted by sales seasonality (SEA_{qt}). 1 is equal to low-season stocks and 10 is equal to high-season stocks. SEA_{qt} is equal to quarterly sales in quarter q year t scaled by annual sales in year t. To reduce the effect of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$ which is average of SEA_{qt} in years t-3 and t-2. I then use $AVGSEA_{qt}$ to predict SEA_{qt} in year t to make sure that information is available to investors when forming portfolios. Panel A shows equal-weighted return and Panel B value-weighted results. Test statistics are in brackets. The data consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 in Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon. The factors are obtained from Kenneth R. French data library.

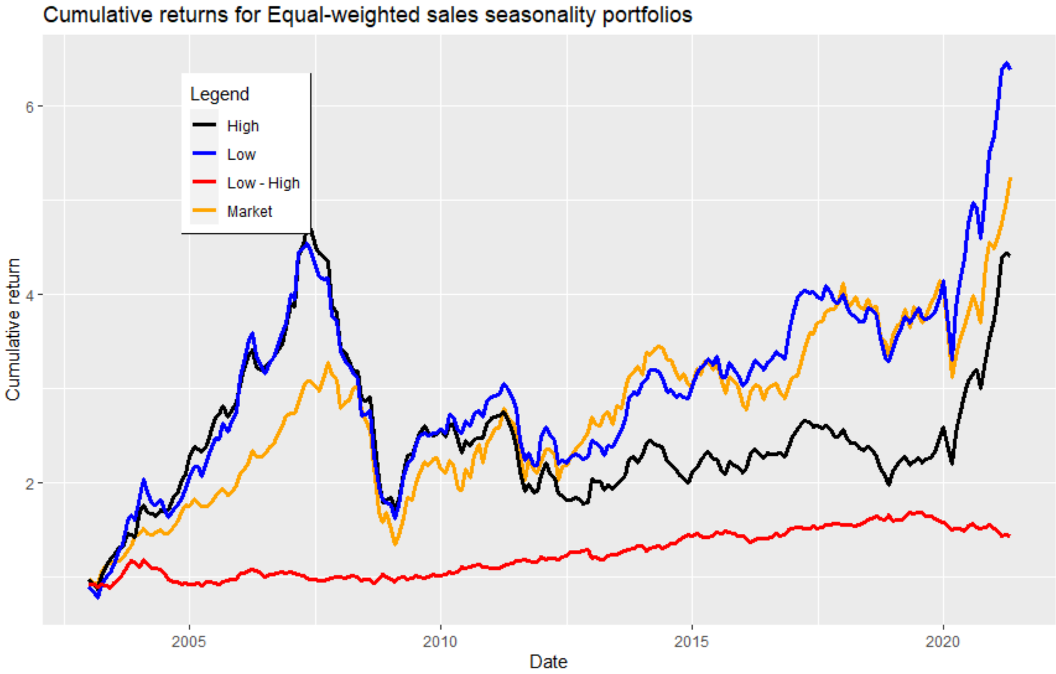
Panel A: EW returns											
	1	2	3	4	5	6	7	8	9	10	L-H
CAPM											
Alpha	0,29	0,45	0,60	0,56	0,62	0,61	0,56	0,36	0,22	0,13	0,15
	[1,09]	[1,93]	[2,72]	[2,63]	[3,12]	[3,17]	[2,88]	[1,86]	[0,98]	[0,58]	[0,98]
Mrktf	0,77	0,72	0,72	0,71	0,72	0,66	0,69	0,69	0,74	0,72	0,05
	[15,57]	[16,37]	[17,34]	[17,65]	[19,34]	[18,31]	[18,86]	[18,91]	[17,63]	[15,90]	[1,54]
Fama-French three-factor											
Alpha	0,15	0,31	0,50	0,46	0,49	0,50	0,49	0,25	0,09	-0,01	0,16
	[0,60]	[1,43]	[2,39]	[2,24]	[2,61]	[2,75]	[2,56]	[1,39]	[0,43]	[-0,05]	[1,02]
Mrktf	0,74	0,68	0,67	0,68	0,71	0,63	0,67	0,66	0,70	0,68	0,06
	[13,72]	[14,56]	[14,95]	[15,44]	[17,72]	[16,41]	[16,28]	[16,82]	[15,66]	[14,11]	[1,81]
SMB	0,69	0,71	0,61	0,53	0,57	0,59	0,42	0,57	0,71	0,78	-0,09
	[5,05]	[6,03]	[5,37]	[4,73]	[5,60]	[6,04]	[4,05]	[5,78]	[6,35]	[6,45]	[-1,11]
HML	0,09	0,12	0,19	0,09	0,00	0,09	0,10	0,11	0,16	0,16	-0,07
	[0,78]	[1,20]	[1,92]	[0,97]	[0,05]	[1,13]	[1,15]	[1,27]	[1,65]	[1,51]	[-0,90]
Fama-French five-factor											
Alpha	0,31	0,44	0,54	0,46	0,53	0,46	0,48	0,25	0,12	0,09	0,22
	[1,18]	[1,95]	[2,44]	[2,09]	[2,69]	[2,43]	[2,37]	[1,28]	[0,55]	[0,39]	[1,30]
Mrktf	0,72	0,66	0,66	0,65	0,69	0,62	0,63	0,64	0,66	0,66	0,06
	[11,87]	[12,50]	[12,96]	[13,04]	[15,21]	[14,05]	[13,71]	[14,44]	[13,08]	[12,13]	[1,58]
SMB	0,66	0,68	0,60	0,51	0,55	0,58	0,40	0,56	0,67	0,76	-0,10
	[4,73]	[5,63]	[5,11]	[4,37]	[5,24]	[5,72]	[3,70]	[5,46]	[5,79]	[6,05]	[-1,08]
HML	-0,17	-0,08	0,09	0,16	-0,06	0,15	0,20	0,11	0,19	-0,02	-0,15
	[-0,94]	[-0,53]	[0,60]	[1,10]	[-0,42]	[1,16]	[1,48]	[0,86]	[1,24]	[-0,15]	[-1,27]
RMW	-0,60	-0,50	-0,21	0,01	-0,19	0,06	0,06	-0,03	-0,12	-0,43	-0,18
	[-2,38]	[-2,30]	[-0,97]	[0,07]	[-1,00]	[0,33]	[0,29]	[-0,16]	[-0,55]	[-1,88]	[-1,10]
CMA	-0,17	-0,20	-0,11	-0,26	-0,17	-0,18	-0,27	-0,15	-0,34	-0,18	0,01
	[-0,74]	[-1,01]	[-0,55]	[-1,37]	[-1,00]	[-1,08]	[-1,57]	[-0,91]	[-1,78]	[-0,88]	[0,08]

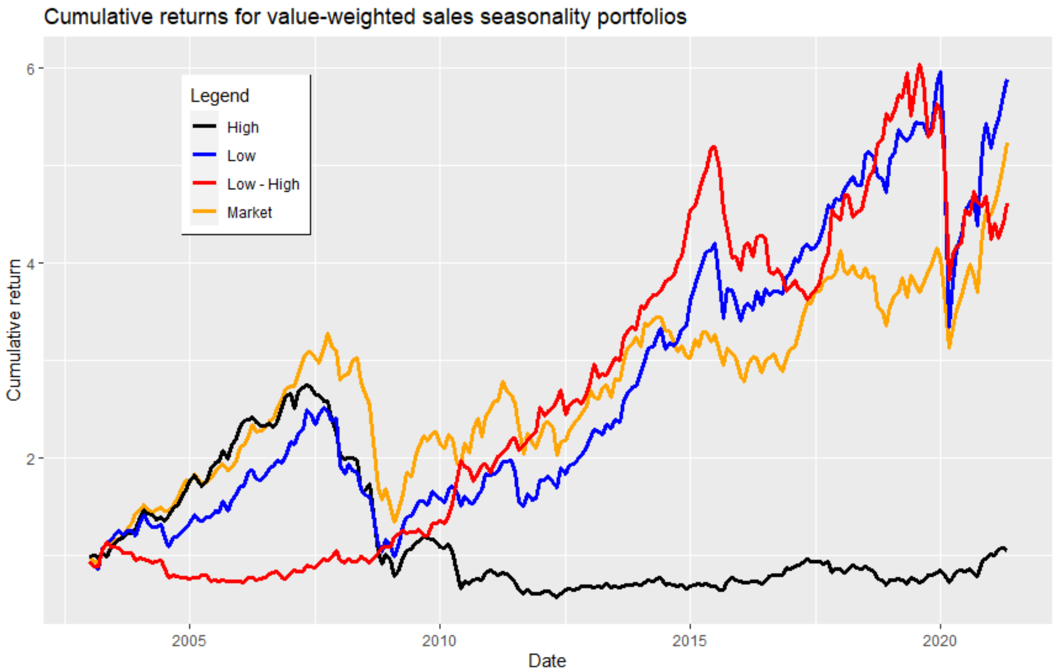
(table continues)

Panel B: VW returns											
	1	2	3	4	5	6	7	8	9	10	L-H
CAPM											
Alpha	0,22	0,55	0,13	0,01	0,29	0,23	0,07	-0,05	0,30	-0,57	0,79
	[0,77]	[2,14]	[0,57]	[0,02]	[1,43]	[1,28]	[0,36]	[-0,22]	[1,28]	[-2,24]	[2,41]
Mrktf	0,87	0,58	0,70	0,55	0,62	0,63	0,60	0,60	0,74	0,84	0,02
	[15,98]	[12,01]	[16,51]	[11,09]	[16,51]	[18,49]	[15,74]	[14,07]	[16,44]	[17,59]	[0,39]
Fama-French three-factor											
Alpha	0,21	0,52	0,14	0,07	0,34	0,23	0,15	-0,02	0,33	-0,57	0,78
	[0,71]	[1,99]	[0,61]	[0,27]	[1,68]	[1,28]	[0,74]	[-0,08]	[1,35]	[-2,22]	[2,34]
Mrktf	0,82	0,61	0,71	0,58	0,62	0,67	0,61	0,62	0,71	0,82	0,00
	[13,24]	[10,86]	[14,58]	[10,38]	[14,33]	[17,29]	[14,13]	[12,93]	[13,80]	[14,82]	[0,06]
SMB	0,23	0,05	-0,09	-0,40	-0,21	-0,15	-0,34	-0,24	0,00	0,10	0,14
	[1,50]	[0,34]	[-0,72]	[-2,81]	[-1,89]	[-1,57]	[-3,16]	[-1,99]	[-0,02]	[0,71]	[0,76]
HML	0,19	-0,11	-0,05	-0,12	0,03	-0,17	-0,01	-0,11	0,11	0,11	0,08
	[1,40]	[-0,91]	[-0,46]	[-1,00]	[0,34]	[-2,02]	[-0,14]	[-1,09]	[0,98]	[0,90]	[0,52]
Fama-French five-factor											
Alpha	0,07	0,38	0,12	-0,03	0,21	0,19	0,02	-0,19	0,29	-0,71	0,78
	[0,23]	[1,39]	[0,49]	[-0,09]	[1,00]	[0,99]	[0,11]	[-0,80]	[1,15]	[-2,62]	[2,22]
Mrktf	0,84	0,62	0,69	0,52	0,60	0,65	0,62	0,66	0,67	0,78	0,06
	[11,93]	[9,75]	[12,47]	[8,39]	[12,34]	[14,90]	[12,71]	[12,07]	[11,52]	[12,58]	[0,78]
SMB	0,28	0,08	-0,10	-0,45	-0,20	-0,16	-0,31	-0,18	-0,03	0,09	0,19
	[1,70]	[0,55]	[-0,82]	[-3,09]	[-1,78]	[-1,59]	[-2,73]	[-1,44]	[-0,19]	[0,60]	[1,03]
HML	0,29	0,05	0,08	0,32	0,35	-0,02	0,18	0,05	0,33	0,47	-0,19
	[1,37]	[0,26]	[0,46]	[1,75]	[2,41]	[-0,19]	[1,22]	[0,29]	[1,89]	[2,58]	[-0,78]
RMW	0,35	0,41	0,13	0,54	0,51	0,20	0,43	0,52	0,21	0,53	-0,17
	[1,21]	[1,54]	[0,57]	[2,06]	[2,50]	[1,09]	[2,13]	[2,28]	[0,87]	[2,04]	[-0,52]
CMA	0,13	0,07	-0,15	-0,45	-0,17	-0,11	0,09	0,25	-0,32	-0,34	0,47
	[0,48]	[0,30]	[-0,72]	[-1,90]	[-0,95]	[-0,66]	[0,48]	[1,21]	[-1,44]	[-1,45]	[1,53]

Graph 1: Cumulative returns of long-short portfolios

This graph shows the cumulative returns of low-season (SEA_{qt}), high-season, low- minus high-season and market portfolios between January 2003 and May 2021. SEA_{qt} is equal to quarterly sales in quarter q year t scaled by annual sales in year t. To reduce the effect of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$, which is average of SEA_{qt} in years t-3 and t-2. I then use the $AVGSEA_{qt}$ to predict SEA_{qt} in year t to make sure that information is available to investors when forming portfolios. The data consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon. The market portfolio is obtained from Kenneth R. French data library.

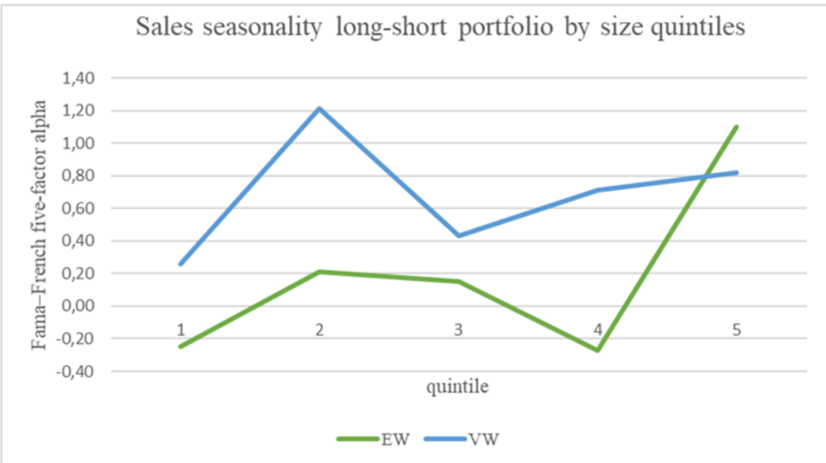




The alphas of equal-weighted and value-weighted portfolios suggest that the sales seasonality premium is driven by larger firms. Graph 2 and Table 3 below show monthly alphas and t-statistics of different size quintiles' sales seasonality premium. I first divide my data into quintiles based on size and then subsequently divide each portfolio into quintiles based on sales seasonality. These findings further strengthen the assumptions that larger firms are receiving more sales seasonality premium and, thus, suggesting that the premium is not caused by the small firm effect. All the size quintiles, expect for the largest one, have statistically insignificant alphas in both equal-weighted and the value-weighted portfolios. The only exception is the second smallest portfolio's value-weighted returns which earn a statistically significant alpha. When considering that, in the same size quintile, equal-weighted portfolio earns no significant alpha, the value-weighted returns are most likely driven by some individual companies. These findings are consistent with Grullon et al. (2020).

Graph 2 and Table 3: Sales seasonality long-short portfolio by size quintiles

These Graph and Table show the difference in the Fama–French five-factor monthly alphas between the low-sales season portfolios and high-sales season portfolios for each size quintile. 1 is equal to the smallest companies while 5 is equal to the largest. Size (ME) is defined as the June market equity of year t and used from July of year t to June of year t + 1. SEA_{qt} is equal to quarterly sales in quarter q year T scaled by annual sales in year T. To reduce the effect of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$ which is average of SEA_{qt} in years t-3 and t-2. I then use $AVGSEA_{qt}$ to predict SEA_{qt} in year t to make sure that information is available to investors when forming portfolios. Exact alphas and t-statistics are reported in the Table. The data consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon. The factors are obtained from Kenneth R. French data library.



	1	2	3	4	5
EW	-0,25	0,21	0,15	-0,27	1,1
	[-0,58]	[0,50]	[0,39]	[-0,75]	[2,98]
VW	0,26	1,21	0,43	0,71	0,82
	[0,54]	[2,14]	[0,86]	[1,37]	[1,94]

To see if the volatility of quarterly sales has an impact to the sales seasonality premium, I create variable SEARANGE which equals the difference between the maximum and minimum values of AVGSEA over the last four quarters. I first test if the volatility of quarterly sales is priced in stocks by allocating stocks into deciles based on their SEARANGE. Table 4 Panel A below presents the results controlled by the Fama-French five-factor model, showing that the companies with highly volatile sales do not earn statistically significant premia over the companies with steady sales; the alpha of low (high) sales volatile firms is 0.04 (0.11) with a t-statistic of 0.22 (0.39). This finding is consistent with Grullon et al. (2020) who find that “quarterly sales volatility by itself is not priced in the cross-section.”.

In Table 4 Panel B and C, I test what kind of effect the sales volatility has on sales seasonality premium by dividing my data in each quarter in half based on SEARANGE and then dividing those two portfolios into deciles based on AVGSEA. Panel B shows the results for the firms below the SEARANGE median. The low-season decile has created an annual alpha of 3.96% (t-statistics = 1.08) and the high-season decile has generated an annual alpha of -2.28% (t-statistics = -0.68), together leading the long-short portfolio with a statistically insignificant annual alpha of 6.24% (t-statistics = 1.40).

On the contrary, Panel C reports a sales seasonality premium over firms above the median SEARANGE. The low-season decile has created an annual alpha of 6.00% (t-statistics = 1.75) and the high-season decile has generated an annual alpha of -3.36% (t-statistics = -0.99), together leading the long-short portfolio with a statistically significant annual alpha of 9.36% (t-statistics = 2.36).

Both findings in Table 4 Panel B and C are consistent with the research carried out by Grullon, Kaba and Núñez-Torres (2020) who do not find any statistically significant evidence from the median sample but similarly find that the sales seasonality premium is created by firms with high- or low-seasons relative to other firms. It is also worth mentioning that among above median SEARANGE firms, the sales seasonality premium is closer to main findings of Grullon et al. (2020) who show that sales seasonality premium is created mainly by the long leg of the portfolio.

Table 4: Sales seasonality premium and variability of sales

This table shows the Fama-French five-factor loadings on value-weighted portfolios sorted by variability of sales. SEA_{qt} is equal to quarterly sales in quarter q year t scaled by annual sales in year t. To reduce the effect of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$ which is an average of SEAqt in years T-3 and T-2. I then use $AVGSEA_{qt}$ to predict SEA_{qt} in year t to make sure that information is available to investors when forming portfolios. SEARANGE is equal to the difference between the maximum and minimum values of AVGSEA over a one-year period. Panel A shows the factor loadings of the portfolios sorted only by SEARANGE. 1 is equal to stocks with the lowest SEARANGE and 10 is equal to stocks with the highest SEARANGE. Panel B shows the factor loadings of the portfolios below the median SEARANGE and sorted by AVGSEA while Panel C shows the factor loadings of the portfolios above the median SEARANGE and sorted by AVGSEA. The test statistics are in brackets. The data consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 in Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon. The factors are obtained from Kenneth R. French data library.

Panel A: SEARANGE											
	1	2	3	4	5	6	7	8	9	10	L-H
Alpha	0,04	0,08	0,10	0,13	0,01	-0,19	0,05	0,13	-0,23	0,11	-0,07
	[0,22]	[0,36]	[0,49]	[0,51]	[0,06]	[-0,82]	[0,23]	[0,51]	[-0,69]	[0,39]	[-0,25]
Mrktf	0,56	0,59	0,65	0,65	0,55	0,62	0,75	0,59	0,79	0,72	-0,17
	[12,50]	[11,59]	[13,98]	[11,45]	[9,25]	[11,31]	[13,64]	[9,77]	[10,17]	[10,97]	[-2,65]
SMB	-0,31	-0,18	-0,19	-0,14	0,00	-0,22	-0,03	-0,25	0,40	0,43	-0,74
	[-3,06]	[-1,50]	[-1,79]	[-1,07]	[-0,01]	[-1,71]	[-0,23]	[-1,78]	[2,23]	[2,85]	[-5,06]
HML	0,10	0,44	0,11	0,28	0,41	0,20	-0,04	0,32	0,65	-0,07	0,17
	[0,75]	[2,86]	[0,82]	[1,61]	[2,28]	[1,20]	[-0,27]	[1,77]	[2,80]	[-0,35]	[0,88]
RMW	0,50	0,92	0,51	0,31	0,41	0,39	0,26	0,35	0,77	-0,41	0,91
	[2,67]	[4,22]	[2,60]	[1,28]	[1,60]	[1,64]	[1,11]	[1,34]	[2,34]	[-1,44]	[3,34]
CMA	0,07	0,14	-0,01	-0,22	0,08	-0,34	-0,17	-0,36	-0,55	-0,70	0,77
	[0,43]	[0,74]	[-0,06]	[-1,05]	[0,37]	[-1,68]	[-0,85]	[-1,61]	[-1,92]	[-2,84]	[3,24]
Panel B: Sales Seasonality within below-median SEARANGE											
	1	2	3	4	5	6	7	8	9	10	L-H
Alpha	0,33	0,08	-0,21	0,34	0,09	-0,24	0,14	0,07	0,15	-0,19	0,52
	[1,08]	[0,29]	[-0,75]	[1,35]	[0,39]	[-1,13]	[0,62]	[0,31]	[0,52]	[-0,68]	[1,40]
Mrktf	0,63	0,62	0,55	0,54	0,60	0,64	0,64	0,55	0,66	0,66	-0,03
	[8,84]	[9,07]	[8,25]	[9,21]	[11,11]	[13,07]	[12,36]	[9,99]	[10,23]	[10,10]	[-0,36]
SMB	0,14	-0,09	-0,37	-0,25	-0,17	-0,26	-0,23	-0,05	-0,24	-0,12	0,26
	[0,88]	[-0,55]	[-2,41]	[-1,82]	[-1,34]	[-2,29]	[-1,95]	[-0,37]	[-1,63]	[-0,77]	[1,30]
HML	0,16	0,23	0,08	0,30	0,20	0,37	0,22	0,05	0,14	0,26	-0,10
	[0,75]	[1,14]	[0,41]	[1,70]	[1,23]	[2,48]	[1,39]	[0,33]	[0,72]	[1,30]	[-0,36]
RMW	-0,01	0,41	0,53	0,47	0,66	0,94	0,49	0,55	0,29	0,54	-0,55
	[-0,05]	[1,40]	[1,87]	[1,86]	[2,86]	[4,47]	[2,22]	[2,35]	[1,05]	[1,91]	[-1,48]
CMA	-0,24	-0,21	0,03	-0,12	0,17	0,05	-0,08	0,41	-0,13	0,08	-0,32
	[-0,89]	[-0,85]	[0,11]	[-0,56]	[0,84]	[0,30]	[-0,43]	[2,01]	[-0,54]	[0,34]	[-0,99]
Panel C: Sales Seasonality within above-median SEARANGE											
	1	2	3	4	5	6	7	8	9	10	L-H
Alpha	0,50	-0,07	0,18	0,25	0,26	0,07	-0,38	0,21	-0,32	-0,28	0,78
	[1,75]	[-0,21]	[0,48]	[0,86]	[0,97]	[0,22]	[-1,31]	[0,71]	[-1,04]	[-0,99]	[2,36]
Mrktf	0,65	0,66	0,63	0,68	0,63	0,70	0,75	0,76	0,78	0,69	-0,04
	[9,69]	[8,42]	[7,09]	[10,18]	[9,90]	[8,93]	[10,96]	[10,83]	[10,74]	[10,60]	[-0,52]
SMB	0,21	0,47	0,34	-0,08	0,06	-0,25	0,01	0,20	0,30	0,04	0,17
	[1,36]	[2,58]	[1,68]	[-0,54]	[0,39]	[-1,36]	[0,08]	[1,25]	[1,80]	[0,27]	[0,96]
HML	0,01	1,03	0,04	0,10	0,14	0,02	0,02	0,16	0,51	0,17	-0,16
	[0,06]	[4,33]	[0,16]	[0,48]	[0,73]	[0,09]	[0,08]	[0,77]	[2,35]	[0,87]	[-0,68]
RMW	0,10	0,99	0,27	0,04	0,31	0,30	0,25	-0,08	0,51	-0,03	0,13
	[0,35]	[2,96]	[0,73]	[0,14]	[1,16]	[0,89]	[0,85]	[-0,28]	[1,62]	[-0,12]	[0,40]
CMA	-0,39	-0,33	0,03	-0,24	-0,43	-0,20	-0,58	-0,39	-0,42	-0,53	0,14
	[-1,55]	[-1,12]	[0,09]	[-0,99]	[-1,83]	[-0,70]	[-2,29]	[-1,52]	[-1,58]	[-2,18]	[0,50]

Following Grullon, Kaba and Núñez-Torres (2020) to further test whether the sales seasonality premium arises from fixed firm characteristics rather than unusual changes in quarterly sales, I form portfolios based on AVGSEAqt on years t-n where n runs from 3 to 7. Table 5 below presents the alphas of both value-weighted and equal-weighted portfolios formed by the stale data. These finding present that practically all the alphas are statistically insignificant. The alphas of Equal-weighted portfolios based on n = 7 are positive and statistically significant which is most likely due to random effects in data as other portfolios do not have significant alphas. Also, as the value-weighted portfolio at n = 7 has an insignificant alpha, the effect in equally weighted portfolio is probably driven by some volatile small firms.

Below Table 5 results on stale data are contradicting with findings of Grullon, Kaba and Núñez-Torres (2020) as they find that $AVGSEA_{qt}$ is a strong and statistically significant predictor even when calculated 20 years in advance. The differences between my and their findings can probably be explained by a lower persistence of companies within sales seasonality portfolios – presented in section 2 – in my data set. I believe that this could be due to a smaller sample and possibly poorer data in Europe than in United States.

Table 5: Predictive power of sales seasonality stale data

This table shows the alphas of the portfolios that buy low-season stocks and short high-season stocks (SEA_{qt}). SEA_{qt} is equal to the quarterly sales in quarter q year t scaled by annual sales in year t. To reduce the effect of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$ which is an average of SEAqt in years t-n and t-n-1. I then use $AVGSEA_{qt}$ to predict SEA_{qt} in year t. The t-statistics are in brackets. The data consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 in Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon. The factors are obtained from Kenneth R. French data library.

	Equal weighted			Value weighted		
n	CAPM	FF3	FF5	CAPM	FF3	FF5
3	0,00	-0,01	0,05	0,43	0,45	0,48
	[-0,01]	[-0,03]	[0,28]	[1,43]	[1,49]	[1,50]
4	0,11	0,15	0,14	0,27	0,23	0,30
	[0,60]	[0,87]	[0,72]	[0,99]	[0,83]	[1,02]
5	0,19	0,26	0,37	0,24	0,17	0,25
	[0,90]	[1,22]	[1,64]	[0,86]	[0,62]	[0,88]
6	0,19	0,28	0,34	-0,10	-0,12	-0,26
	[0,91]	[1,41]	[1,58]	[-0,28]	[-0,34]	[-0,70]
7	0,60	0,61	0,55	0,17	0,26	0,24
	[2,61]	[2,60]	[2,25]	[0,49]	[0,73]	[0,64]

3.2 Correlation with other asset pricing factors and seasonalities

As tested by Grullon, Kaba and Núñez-Torres, I also conduct tests to see whether the sales seasonality is correlated with generally used asset pricing factors. To measure this, I calculate Pearson correlation coefficients between the existing asset pricing factors and SEAF factor which is the low-sales season portfolio minus the high-sales season portfolio and is created by the Fama-French convention. All the variables are defined in Appendix. Table 6 reports the correlation between SEAF and excess market return, small minus big, high minus low, robust minus weak, conservative minus aggressive, momentum winner minus losers, and SEAS which is a factor of past same calender month winners minus losers, created in the Fama French convention in order to observe the correlation between sales seasonality and seasonality presented by Heston and Sadka (2008).

Table 6 Panel A shows that SEAF is uncorrelated with these factors, as also reported by Grullon, Kaba and Núñez-Torres (2020). I also calculated arithmetic means, standard deviations, and Sharpe ratios for all of these factors. Panel B reports these calculations. Conversely to the findings of Grullon, Kaba and Núñez-Torres (2020, the SEAF measured by Sharpe ratio has performed quite poorly in Europe, beating only HML, CMA and SEAS, out of which HML and CMA have negative alphas.

Table 6: Correlation and performance of different factors

This table shows the correlation and performance of the Fama French five-factors, momentum, seasonality (SEAS), and sales seasonality (SEAF). Panel A presents Pearson's correlation coefficients between different factors and SEAF which is a factor-based measure of sales seasonality (low minus high), created in the Fama French convention. Panel B reports monthly means, standard deviations, and annualized Sharpe ratios for each factor. Mrktf is market excess return, SMB is small minus big, HML is high minus low, RMW is robust minus weak, CMA is conservative minus aggressive, WML is momentum winner minus losers, and SEAS is factor-based measure of seasonality (winners minus losers), created in the Fama French convention. The data consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon. The Fama French five-factors and momentum are obtained from Kenneth R. French data library.

Panel A: Pearson correlation coefficients

Variable	Mrktf	SMB	HML	RMW	CMA	WML	SEAS
SEAF	-0,020	0,060	-0,008	-0,041	0,050	-0,034	0,091

Panel B: Sharpe ratios

Variable	Mean%	Std dev	Annualized Sharpe ratio
Mrktf	0,79	5,27	0,52
SMB	0,28	1,80	0,53
HML	-0,02	2,43	-0,03
RMW	0,30	1,50	0,68
CMA	-0,04	1,38	-0,11
WML	0,69	3,84	0,62
SEAS	0,52	5,38	0,33
SEAF	0,31	2,77	0,39

4.Economic mechanisms

4.1 Overview

In this Section, I follow Grullon et al. (2020) to examine possible reasons behind the sales seasonality premium. I will first investigate whether real options can explain the sales seasonality premium. If firms increase their investments during their high-seasons, it could lead a lower expected return during these seasons as they have converted their growth opportunities into assets (Berk, Green and Naik, 1999). Further logic – presented by Berk et al. (1999) – behind this theory is that firms do prefer investments which have lower systematic risk, keeping all else equal. After investing, a firm's assets have lower systematic risk leading to lower expected return in future periods. If this theory holds, I should find positive correlations between the sales seasonality and investments.

I will also investigate the correlation between changes in leverage and the sales seasonality. If the correlation is negative, it would support a theory that the sales seasonality premium is created by the effect of leverage to systematic risk.

In addition, I examine whether investor attention varies between sales seasons. The theory behind this is that some investors tend to overweight neglected stocks which leaves them more vulnerable to idiosyncratic risk (Merton 1987). As discussed by Grullon et al. (2020), Merton's equation shows that these investors demand risk-premium of:

$$R_k - R_k^* = \delta \chi_k \sigma_k^2 \frac{(1-q_k)}{q_k} \frac{R_k^*}{R_k} \qquad (1)$$

where R_k is the incomplete information expected return, R_k^* is the complete information expected return, δ is the representative investor's degree of risk aversion, χ_k is the is the fraction of the market portfolio invested in security k, σ_k^2 is idiosyncratic volatility of security k and q_k is the fraction of all investors who know about security k. If investor attention increases during high season the risk premia should be lower. This equation also shows that the risk-premium increases with size and idiosyncratic volatility. Thus, if the equation holds, the sales seasonality premium should be higher with large stocks with high idiosyncratic volatility as overweighting them have higher effect on portfolios idiosyncratic risk than overweighting smaller stock.

Further following Grullon et. al. (2020), theory based on Barber and Odean (2008) states that low season may bring noise traders to stocks that push the prices above fundamentals. If this theory holds, it could explain the sales seasonality premium and I should observe a spike in trading volume of low-season stocks.

I also examine whether dispersion among investors varies based on sales seasons. This perspective relies on the theory that, when dispersion is high, investors demand a risk-premium due to overconfident investors bringing more volatility into stock (Dumas, Kurshev and Uppal, 2009) or due to the risk of trading against investors with more influence on stock prices (David, 2008). Further, when combining short-selling constraints and higher dispersion in expectations, a stock could become overvalued as it reflects only optimistic investors belief (Miller, 1997). Therefore, if dispersion is lower during high season, these theories support lower returns observed during such seasons.

4.2 Investment and financing decisions and sales seasonality

Next, I will investigate how companies invest and finance in different sales seasons. I do this by conducting panel data regression with several estimates for investment and financing decisions on sales seasonality while controlling for size, book-to-market, profitability, firm-fixed, and year-fixed effects. I conduct the test for both contemporaneous SEA_q and SEA_{q+1} to examine companies advance preparation for futures period.

I estimate investments by calculating changes in quarter q and q-1 in total assets (IAQ), current assets (ICAQ), net property plant and equipment (PPEQ), and inventories (INVQ). On the other hand, I estimate financing decisions by changes in quarter q and q-1 in book leverage (BL) which is total debt divided by the total assets and market leverage (ML) which, in turn, is equal to total debt divided by market value. All the variables are defined in the Appendix.

Below Table 7 Panel A shows estimates of the relation between the sales seasonality and investments. Consistent with the real option theory and the Grullon, Kaba and Núñez-Torres (2020), first three variables – IAQ, ICAQ and PPEQ – have positive and statistically significant coefficient on SEA_q, suggesting that firms invest more during their high-seasons. Also consistent with Grullon et al. (2020), investment measured by change in total assets and current assets have statistically significant and positive coefficients for SEA_{q+1}, suggesting that firms also invest prior to their high-seasons. The coefficient for change in inventories on SEA_q is negative – as in study of Grullon et al. (2020), who show that firms use their inventories during high seasons – but in my study it is statistically insignificant. Also, as the coefficient of INVQ on SEA_{q+1} is positive – as in study of Grullon et al.

(2020), who shows that firms stockpile inventories before high season – but again, the coefficient is statistically insignificant.

To test the correlation between the portfolios sorted by AVGSEA and assets change, I form ten portfolios on month t based on average quarterly total assets growth in quarters q-5. The results are shown in below Table 8 where, after controlling for the Fama-French five-factors, the low AVGSEA portfolio has a Pearson correlation coefficient of 0.44 (t-statistics = 6.97) with low total assets change portfolio, while the high AVGSEA portfolio has a correlation of 0.32 (t-statistics = 4.80) with the high total assets change portfolio. These findings are partially in line with Grullon et al. (2020) who find, in their untabulated results, that their sample high AVGSEA portfolio has a correlation of 0.38 with the high total assets change portfolio, but they report no significant correlation between the low AVGSEA portfolio and the low total assets change portfolio. Therefore, they state that even though their findings support the real options theory, they cannot find it to be entire satisfactory as large part of the premium arises from the long leg of the portfolio which returns are uncorrelated with the returns of the low assets change portfolio. However, in Europe, the situation is different from two perspectives: first, the majority of sales seasonality premium originates from the short leg and, second, both the portfolios are significantly correlated with the corresponding assets change portfolio. Thus, the real-option theory can be considered as a potential explanation for the sales seasonality premium in Europe.

Table 7 Panel B presents the estimates of financing variables. Like in study of Grullon et.al. (2020), both the coefficient of changes in book leverage and market leverage on SEA_q are negative. However, in my study the coefficients are statistically insignificant. Opposite effect can be found in coefficients of BL change and ML change on SEA_{q+1}, where, again, coefficients are statistically insignificant. Thus, changes in capital structure do not provide sufficient information in order to explain sales seasonality premium.

Table 7: Investments, financing and sales seasonality

This table shows the relation between investment and financing decisions and the sales seasonality. SEA_{qt} is equal to quarterly sales in quarter q year t scaled by annual sales in year t. SEA_{q+1} is one-period-ahead value of SEA_{qt}. Panel A shows the regression results between the sales seasonality and investment variables. IAQ is relative change of total assets from quarter q-1 to quarter q. ICAQ is relative change in current assets from quarter q-1 to quarter q. PPEQ is relative change in net property, plant and equipment between quarters q-1 and q. INVQ is relative change in current assets from quarter q-1 to quarter q. Panel B shows the regression results between sales seasonality and financing. BL Change is change in book leverage measured by total debt divided by total assets between quarters q-1 and q. ML Change is change in market leverage measured by total debt divided by the market value of equity between quarter q-1 and q. Total debt is defined as total long-term liabilities plus long-term debt in current liabilities. The control variables are log of market value (logME), book-to-market (BM), and gross profits-to-assets (GPA). I also control for firm and year fixed effects. Test statistics are in brackets. Data – collected from Eikon – consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon.

Panel A: Investment variables

	IAQ		ICAQ		PPEQ		INVQ	
SEAq	0,49		0,64		8,01		-5,75	
	[6,32]		[10,77]		[7,55]		[-1,23]	
SEAq+1		0,21		0,31		-0,61		1,3
		[2,56]		[4,94]		[-0,55]		[0,26]
R^2	0,108	0,117	0,179	0,192	0,174	0,143	0,039	0,038
Observations	71 689	69 322	71 560	69 190	69 078	66 786	59 820	57 902

Panel B: Financing variables

	BL Change		ML Change	
SEAq	-1,79		-0,35	
	[-0,28]		[-0,49]	
SEAq+1		0,1		0,45
		[0,03]		[0,08]
R^2	0,032	0,040	0,062	0,062
Observations	59 929	57 932	50 130	49 316

Table 8: Correlation of AVGSEA portfolios and portfolios based on assets change

This table shows the partial correlation of returns between low-season portfolio (SEA_{qt}) and low total assets change portfolio as well as high-season portfolio and high total assets change portfolio. SEAqt is equal to quarterly sales in quarter q year t scaled by annual sales in year t. To reduce the effect of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$ which is average of SEA_{qt} in years t-3 and t-2. I then use $AVGSEA_{qt}$ to predict SEA_{qt} in year t and divide stocks into deciles to make sure that information is available to investors when forming portfolios. Similarly, I sort stocks into deciles based on their average assets change (IAQ) during last five quarters. The controlling variables are excess market return, SMB, HML, CMA, and RMW. Test statistics are in brackets. The data – collected from Eikon – consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon.

Correlation of portfolios based on assets change and AVGSEA

	Low AVGSEA		High AVGSEA
Low assets change	0,44	High assets change	0,32
	[6,97]		[4,80]

4.3 Stock market activity and sales seasonality

Next, I will investigate the relationship between stock market activity and sales seasonality. As discussed earlier, temporarily neglected stocks receive a risk-premium in a model developed by Merton (1987). Therefore, if the investor attention declines during low-season, it could explain better performance over high-season. I estimate investor attention by trading volume, more specifically turnover by volume divided by the total amount of shares outstanding (STURN). Table 9 below shows that the coefficient of turnover on SEAq is positive and statistically significant and correlated with sales seasonality, supporting the assumption that firms are more neglected during their low season. When considering SEAq+1, the coefficient is statistically insignificant. Both the findings concerning STURN are consistent with Grullon et.al. (2020) who also find a positive correlation between the STURN and SEAq.

In addition, I test whether a firm's illiquidity plays role in the sales seasonality premium. I do this by Amihud's illiquid measure (ILLIQ). The results are reported in Table 9 below. I find negative coefficients – as I should in order to support the theory that stocks are less liquid during their low-season and, thus, due to illiquidity premium they would have higher expected return (Amihud, 2002). However, the coefficients on SEAq and SEAq+1 are both statistically insignificant. In their study, Grullon et al. (2020) expect to find negative correlation between ILLIQ and SEAq but instead they find the correlation to be positive in their sample, and thus could not explain sales seasonality premium with illiquidity premium.

I further test if disagreement, measured by dispersion in analyst earning forecast (i.e. the standard deviation of earnings forecasts divided by the absolute value of the consensus mean forecast, measure created by Diether, Malloy and Scherbina (2002)), could explain the sales seasonality premium. Indeed, as shown in Table 9 below, I find that the coefficient of dispersion on SEA_q is negative and statistically significant which is in line with the previously mentioned theories of Dumas et al. (2009), David (2008), and Miller (1977) to explain the sales seasonality premium. Opposite to my findings, Grullon et al. (2020) find that, in their sample, dispersion has a positive correlation with SEA_q and, therefore, they can not explain the sales seasonality premium with it. However, it is worth mentioning that my sample of analyst dispersion is rather small, consisting of approximately 15,000 observations and, thus, also some idiosyncratic factors could drive the results.

I also estimate investor attention by season with change in shares under institutions management. Variable INST Change shows negative but statistically insignificant coefficient on both SEA_q and SEA_{q+1}. These findings – because insignificant – can not offer support for neglected stock hypothesis and they are also not in line with Grullon et al. (2020) as they find a similar variable, which measures number of institutions holding the stock, to be positive and statistically significant. This causes further suspicions about sales seasonality originating from neglected stocks in Europe.

Table 9: Investor attention, stock market activity, information environment and sales seasonality

This table shows the relation between investor attention, stock market activity, information environment, and sales seasonality. SEA_{qt} is equal to quarterly sales in quarter q year t scaled by annual sales in year t. SEAq+1 is one-period-ahead value of SEA_{qt}. STURN is share turnover measured by volume divided by shares outstanding. ILLQ is Amihud's illiquidity measure. DISP is dispersion in analyst estimates for earnings measured by standard deviation of estimates divided by absolute mean of estimates from IBES. INST change is relative change of stocks in institutional holding. The control variables are log of market value (logME), book-to-market (BM), and gross profits-to-assets (GPA). I also control for firm and year fixed effects. Data – collected from Eikon – consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 in Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon.

Proxies for stock market activity and investors information environment								
	STURN		ILLIQ		DISP		INST Change	
SEAq	7,110		-0,440		-0,025		-0,432	
	[2,48]		[-0,68]		[-3,12]		[-0,15]	
SEAq+1		-0,52		-0,58		0,01		-2,160
		[-0,17]		[-0,94]		[0,91]		[-0,68]
R^2	0,024	0,025	0,572	0,560	0,075	0,047	0,024	0,025
Observations	55 080	52 889	67 232	64 951	15 093	14 727	53 841	51 660

4.4 Stock price efficiency

I further test neglected stock hypothesis to see whether low-season stocks incorporate new information less efficiently than high-season stocks. Following Grullon et al. (2020), I estimate stock market efficiency by post earnings announcement market adjusted average cumulative abnormal returns (CARs) from January 2003 to June 2021. As my data set is smaller than one used by Grullon et.al. (2020), I divide stocks into five portfolios based on their AVGSEA measure compared to ten portfolios used by them[4]. The results are plotted for both negative and positive surprises in below Graph 3 which shows the returns from day t+2 to t+45, where t is the announcement day.

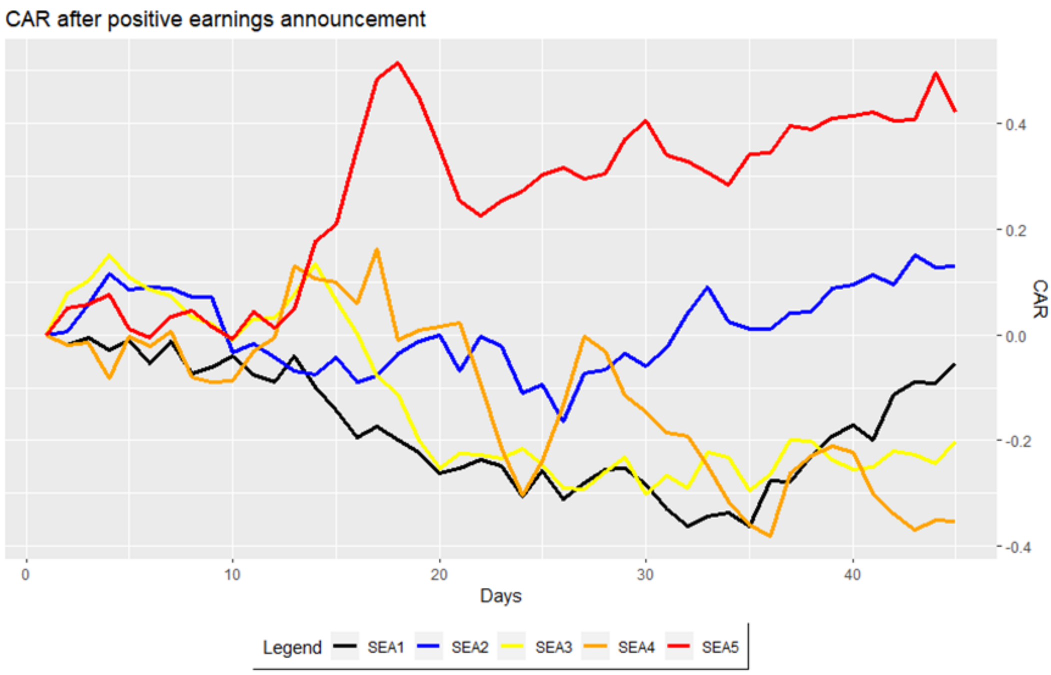
Opposite to Grullon et al. – who find that high-season stocks faced the smallest drift and low-season stocks the highest drift – and the neglected stocks hypothesis, the high-season stocks have the highest cumulative abnormal return after positive announcement and low-season have even slightly negative CAR. On the other hand, after negative earnings announcement, I find some support to neglected

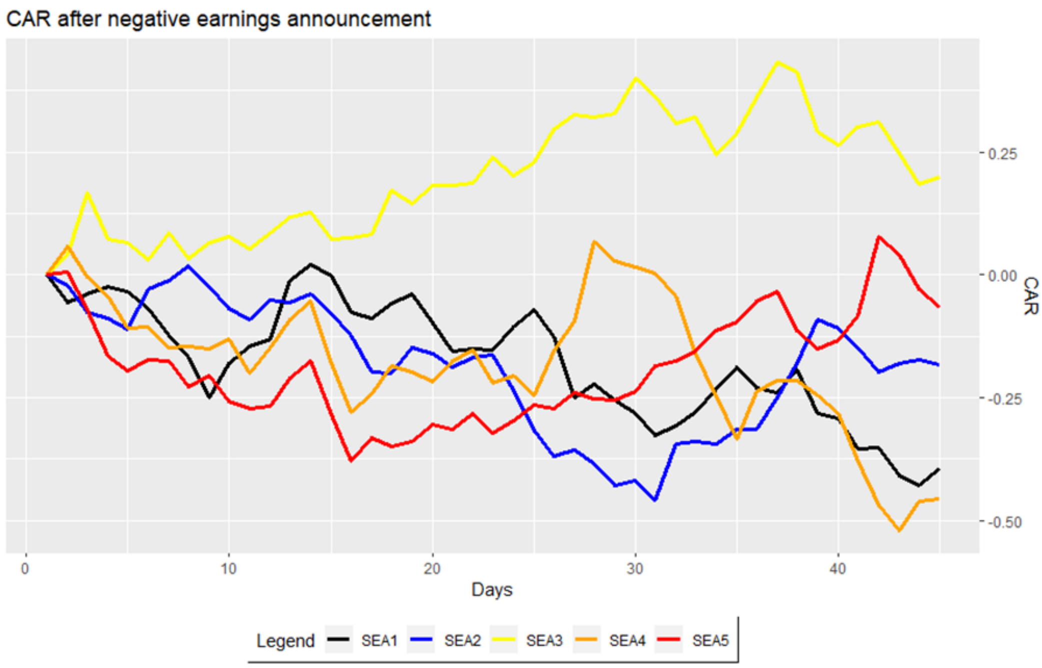
[4] The results do not change significantly even if I use ten portfolios.

stock hypothesis because high-season portfolio face CAR only close to zero per cent while low-season portfolio has CAR about -0.40. Although low-season does not have the strongest drift, it suggests that, at least after negative earnings announcement, low-season stocks tend to be less efficient than high-season stocks.

Graph 3: Cumulative abnormal returns of sales seasonality portfolios after earnings announcements

This graph shows earnings announcement market-adjusted average cumulative abnormal returns percentage (CARs) for positive and negative surprise for five portfolios sorted on sales seasonality (SEA). CARs are plotted from day 2 (t+2) from earnings announcement until day 45 (t+45). The data – collected from Eikon – consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon.





4.5 Incomplete market risk premium

Merton's (1987) model predicts that the neglected stocks' risk premium is increasing with size and idiosyncratic volatility. To test this, I follow Grullon et.al. (2020) and divide stocks first into two portfolios based on their size and then divide them further in half based on idiosyncratic volatility, measured by the standard deviation of residuals of CAPM. I calculate the difference in alphas between the lowest and highest quintiles of sales seasonality within each of the four size-volatility portfolios. If the sales seasonality premium is due to large, neglected stocks, I should observe most of the effect originating in the large high-volatility portfolio. Table 10 below reports the result. Contradicting to Grullon et. al. (2020) and their prediction that the sales seasonality premium is due to large, neglected stock, I find that none of these portfolios have statistically significant alphas. However, the coefficient is smallest with small firms with low idiosyncratic volatility. As all the alphas are statistically insignificant, these findings contradict with Merton's (1987) model as an explanation for sales seasonality premium and, thus, it contradicts with the neglected stock hypothesis.

Table 10: Effect of size and idiosyncratic volatility on sales seasonality premium

This table shows the differences between the value-weighted alphas of the lowest and highest quintiles of sales seasonality within portfolios based on size and idiosyncratic volatility. First, I divide my sample in half based on companies' size and, then, divide both the size portfolios in half based on idiosyncratic volatility. Size (ME) is defined as the June market equity of year t and used from July of year t to June of year t+1. Idiosyncratic volatility (IVOL) is defined as the standard deviation of the residuals for each firm of a monthly CAPM regression of month t-1. Test statistics are in brackets. SEAqt is equal to quarterly sales in quarter q year t scaled by annual sales in year t. To reduce the effect of the outliers or short-term shocks, I calculate variable $AVGSEA_{qt}$, which is average of SEA_{qt} in years t-3 and t-2. I then use $AVGSEA_{qt}$ to predict SEA_{qt} in year t to make sure that information is available to investors when forming portfolios. I then divide stocks into quintiles based on $AVGSEA_{qt}$. The data – collected from Eikon – consist of all the primary listed and delisted nonfinancial companies between years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon.

Size and volatility portfolios					
Fama-French three-factor model			Fama-French five-factor model		
	Low IVOL	High IVOL		Low IVOL	High IVOL
Low ME	0,01	0,33	Low ME	0,04	0,49
	[0,03]	[1,02]		[0,12]	[1,46]
High ME	0,40	0,41	High ME	0,47	0,36
	[1,37]	[1,41]		[1,54]	[1,16]

5. Conclusion

Based on my results, sales seasonality predicts future returns also in Europe. By sorting stocks based on sales seasonality at the beginning of each month and going long on stocks at their low-season and shorting stocks at their high-season has generated an annual alpha of 9.36% from January 2003 to June 2021 driven mostly by large firms with relatively high or low seasons compared to other companies. Factor based sales seasonality is uncorrelated with the Fama-French five factors, momentum and previously documented seasonality where firms receive abnormal returns same month every year.

Possible explanations for the phenomena are firms' investment decisions, capital structure, investor attention, and/or analyst dispersion. I find the strongest evidence explaining sales seasonality premium to be the firms' investment behaviour which I present to be pro-seasonal which can cause counter-seasonal returns due to real option theory. The second strongest evidence that I find relates to the theory in dispersion in analyst estimates, which are counter seasonal. In addition, I find some evidence that high-season firms have higher levels of investor attention. I do not find any strong evidence to support the theory of fluctuation in capital structure. Even though these findings provide many possible explanations for the sales seasonality premium, also the behavioural biases could cause the sales seasonality premium, as also considered by Grullon et al. (2020).

Appendix

This part of the study shows the value-weighted factor loadings for seasonalities calculated with the cost of goods sold, selling, general and administrative expenses, operational cashflows, and net profits, as well as defines all the variables used throughout the paper.

Table A1: The predictive power of sales seasonality by different variables

This table shows the factor loadings of portfolios sorted by seasonality (SEA_{qt}). 1 is equal to low-season stocks and 10 is equal to high-season stocks. SEA_{qt} is equal to quarterly variable in question in quarter q year t scaled by annual variable in year t. To reduce the effects of the outliers and short-term shocks, I calculate variable $AVGSEA_{qt}$ which is an average of SEAqt in years t-3 and t-2. I then use $AVGSEA_{qt}$ to predict SEA_{qt} in year t to make sure that information is available to investors when forming portfolios. Panel A shows the value-weighted return based on the cost of goods sold, Panel B shows the value-weighted results based on selling, general and administrative expenses, Panel C shows value-weighted results based on operating cashflows, and Panel D shows value-weighted results based on net profits. The data consist of all the primary listed and delisted nonfinancial companies during years January 2000 - June 2021 from Finland, Sweden, Norway, Denmark, Germany, Poland, Netherlands, France, United Kingdom, Italy, and Spain. I exclude stocks that do not have RIC-code linked in Eikon. The factors are obtained from Kenneth R. French data library.

Panel A: VW returns sorted by COGS											
	1	2	3	4	5	6	7	8	9	10	L-H
CAPM											
Alpha	0,30	0,53	0,22	0,14	0,19	0,11	0,19	0,14	0,07	0,04	0,26
	[0,96]	[1,81]	[0,77]	[0,53]	[0,86]	[0,51]	[0,89]	[0,52]	[0,28]	[0,13]	[0,67]
Mrktf	0,82	0,67	0,65	0,63	0,61	0,63	0,62	0,58	0,70	0,86	-0,04
	[14,03]	[12,30]	[12,01]	[12,81]	[14,86]	[16,10]	[15,69]	[11,80]	[14,70]	[14,97]	[-0,62]
Fama-French three-factor											
Alpha	0,24	0,57	0,22	0,17	0,24	0,12	0,24	0,19	0,10	0,02	0,21
	[0,76]	[1,96]	[0,76]	[0,65]	[1,10]	[0,58]	[1,17]	[0,73]	[0,39]	[0,08]	[0,55]
Mrktf	0,85	0,59	0,66	0,68	0,60	0,67	0,65	0,55	0,67	0,84	0,01
	[12,74]	[9,49]	[10,51]	[11,99]	[12,87]	[15,09]	[14,66]	[9,75]	[12,27]	[12,79]	[0,15]
SMB	0,13	0,13	-0,02	-0,28	-0,21	-0,22	-0,36	-0,13	-0,03	0,12	0,01
	[0,76]	[0,86]	[-0,12]	[-1,99]	[-1,77]	[-1,93]	[-3,22]	[-0,90]	[-0,18]	[0,71]	[0,05]
HML	-0,16	0,36	-0,03	-0,17	0,04	-0,17	-0,12	0,14	0,12	0,05	-0,22
	[-1,13]	[2,71]	[-0,20]	[-1,39]	[0,35]	[-1,77]	[-1,23]	[1,15]	[1,03]	[0,36]	[-1,19]
Fama-French five-factor											
Alpha	0,31	0,29	0,06	0,09	0,15	0,00	0,18	0,06	-0,08	0,12	0,19
	[0,94]	[0,95]	[0,20]	[0,31]	[0,65]	[0,00]	[0,82]	[0,23]	[-0,32]	[0,38]	[0,46]
Mrktf	0,88	0,58	0,69	0,62	0,62	0,66	0,64	0,57	0,63	0,78	0,11
	[11,61]	[8,45]	[9,71]	[9,82]	[11,58]	[13,20]	[12,67]	[8,84]	[10,39]	[10,43]	[1,14]
SMB	0,16	0,17	0,04	-0,33	-0,17	-0,21	-0,35	-0,09	-0,03	0,04	0,11
	[0,89]	[1,05]	[0,24]	[-2,25]	[-1,41]	[-1,79]	[-3,03]	[-0,57]	[-0,24]	[0,25]	[0,52]
HML	-0,43	0,82	0,09	0,24	0,14	0,09	0,07	0,29	0,59	0,16	-0,59
	[-1,89]	[4,02]	[0,44]	[1,28]	[0,88]	[0,58]	[0,47]	[1,50]	[3,25]	[0,74]	[-2,11]
RMW	-0,35	0,93	0,45	0,48	0,29	0,46	0,29	0,40	0,72	-0,17	-0,18
	[-1,10]	[3,24]	[1,50]	[1,80]	[1,30]	[2,19]	[1,37]	[1,48]	[2,82]	[-0,56]	[-0,45]
CMA	0,25	-0,10	0,23	-0,45	0,11	-0,08	-0,08	0,12	-0,35	-0,52	0,77
	[0,86]	[-0,38]	[0,86]	[-1,88]	[0,56]	[-0,42]	[-0,41]	[0,49]	[-1,51]	[-1,86]	[2,16]

(table continues)

Panel B: VW returns sorted by seasonality measured by sgae											
	1	2	3	4	5	6	7	8	9	10	L-H
CAPM											
Alpha	0,61	0,16	0,38	0,23	0,03	-0,03	0,04	0,42	0,01	-0,09	0,70
	[1,62]	[0,58]	[1,19]	[0,86]	[0,11]	[-0,10]	[0,14]	[1,44]	[0,02]	[-0,35]	[1,68]
Mrktf	0,75	0,61	0,77	0,67	0,72	0,77	0,74	0,77	0,75	0,69	0,06
	[10,65]	[11,59]	[12,92]	[13,44]	[12,68]	[13,81]	[13,50]	[13,90]	[12,95]	[14,37]	[0,81]
Fama-French three-factor											
Alpha	0,55	0,09	0,41	0,20	0,03	-0,08	0,10	0,46	0,03	-0,07	0,62
	[1,45]	[0,32]	[1,28]	[0,75]	[0,10]	[-0,26]	[0,34]	[1,54]	[0,09]	[-0,27]	[1,48]
Mrktf	0,77	0,59	0,75	0,69	0,73	0,75	0,71	0,77	0,73	0,65	0,13
	[9,50]	[9,83]	[10,81]	[11,96]	[11,17]	[11,72]	[11,38]	[12,04]	[10,89]	[11,75]	[1,41]
SMB	0,17	0,39	-0,04	0,05	-0,03	0,28	-0,17	-0,14	-0,01	0,08	0,08
	[0,81]	[2,60]	[-0,22]	[0,37]	[-0,19]	[1,71]	[-1,05]	[-0,89]	[-0,04]	[0,60]	[0,37]
HML	-0,10	0,07	0,13	-0,08	-0,05	0,08	0,11	0,02	0,10	0,18	-0,28
	[-0,56]	[0,57]	[0,84]	[-0,65]	[-0,35]	[0,57]	[0,85]	[0,11]	[0,71]	[1,54]	[-1,45]
Fama-French five-factor											
Alpha	0,60	0,05	0,30	0,21	-0,03	-0,17	0,06	0,51	-0,13	-0,08	0,68
	[1,49]	[0,15]	[0,90]	[0,74]	[-0,09]	[-0,54]	[0,19]	[1,62]	[-0,39]	[-0,29]	[1,54]
Mrktf	0,82	0,60	0,68	0,69	0,77	0,75	0,76	0,77	0,81	0,62	0,19
	[8,82]	[8,81]	[8,77]	[10,42]	[10,31]	[10,28]	[10,74]	[10,51]	[10,65]	[9,92]	[1,90]
SMB	0,21	0,40	-0,08	0,05	0,01	0,28	-0,10	-0,14	0,09	0,06	0,15
	[0,99]	[2,55]	[-0,43]	[0,33]	[0,03]	[1,65]	[-0,59]	[-0,82]	[0,51]	[0,42]	[0,64]
HML	-0,39	0,04	0,58	-0,09	-0,11	0,20	-0,03	-0,05	0,02	0,29	-0,68
	[-1,40]	[0,22]	[2,54]	[-0,44]	[-0,50]	[0,95]	[-0,13]	[-0,22]	[0,10]	[1,58]	[-2,25]
RMW	-0,31	0,06	0,53	-0,03	0,10	0,28	0,02	-0,16	0,31	0,08	-0,39
	[-0,81]	[0,20]	[1,64]	[-0,11]	[0,33]	[0,93]	[0,06]	[-0,54]	[0,99]	[0,31]	[-0,92]
CMA	0,34	0,08	-0,55	-0,03	0,29	-0,04	0,42	0,00	0,59	-0,21	0,55
	[0,98]	[0,31]	[-1,89]	[-0,14]	[1,03]	[-0,13]	[1,56]	[-0,02]	[2,07]	[-0,88]	[1,44]

Panel C: VW returns sorted by seasonality measured by operating cashflow											
	1	2	3	4	5	6	7	8	9	10	L-H
CAPM											
Alpha	0,15	0,12	0,13	0,17	0,00	-0,03	0,52	0,03	0,38	-0,05	0,20
	[0,56]	[0,41]	[0,48]	[0,66]	[0,00]	[-0,12]	[1,68]	[0,13]	[1,50]	[-0,20]	[0,66]
Mrktf	0,67	0,53	0,49	0,56	0,53	0,52	0,54	0,61	0,53	0,60	0,08
	[13,64]	[9,77]	[10,19]	[11,57]	[9,84]	[11,27]	[9,24]	[14,35]	[11,29]	[13,08]	[1,37]
Fama-French three-factor											
Alpha	0,12	0,16	0,07	0,23	0,13	0,07	0,59	0,08	0,44	-0,05	0,17
	[0,45]	[0,55]	[0,26]	[0,90]	[0,47]	[0,30]	[1,89]	[0,36]	[1,74]	[-0,22]	[0,57]
Mrktf	0,72	0,57	0,55	0,59	0,51	0,53	0,57	0,61	0,55	0,62	0,09
	[12,66]	[9,14]	[9,91]	[10,74]	[8,43]	[10,32]	[8,52]	[12,47]	[10,38]	[11,86]	[1,47]
SMB	-0,05	-0,31	0,04	-0,37	-0,49	-0,48	-0,39	-0,21	-0,34	-0,08	0,03
	[-0,32]	[-2,01]	[0,29]	[-2,64]	[-3,19]	[-3,68]	[-2,31]	[-1,72]	[-2,52]	[-0,61]	[0,21]
HML	-0,19	-0,14	-0,25	-0,11	0,12	-0,03	-0,10	0,02	-0,08	-0,11	-0,08
	[-1,56]	[-1,05]	[-2,05]	[-0,93]	[0,89]	[-0,27]	[-0,67]	[0,22]	[-0,73]	[-0,96]	[-0,59]
Fama-French five-factor											
Alpha	0,00	0,06	-0,11	0,05	-0,23	-0,19	0,48	0,07	0,40	-0,07	0,08
	[0,01]	[0,21]	[-0,41]	[0,20]	[-0,77]	[-0,76]	[1,45]	[0,27]	[1,55]	[-0,28]	[0,24]
Mrktf	0,74	0,53	0,54	0,56	0,56	0,52	0,62	0,60	0,48	0,62	0,12
	[11,49]	[7,55]	[8,63]	[9,14]	[8,39]	[9,27]	[8,23]	[10,66]	[8,05]	[10,29]	[1,69]
SMB	-0,01	-0,35	0,04	-0,39	-0,38	-0,44	-0,31	-0,21	-0,40	-0,09	0,08
	[-0,04]	[-2,18]	[0,30]	[-2,73]	[-2,42]	[-3,35]	[-1,77]	[-1,66]	[-2,90]	[-0,65]	[0,50]
HML	-0,10	0,23	0,09	0,36	0,53	0,45	-0,11	0,14	0,32	-0,04	-0,06
	[-0,52]	[1,10]	[0,48]	[1,98]	[2,65]	[2,69]	[-0,50]	[0,82]	[1,82]	[-0,21]	[-0,29]
RMW	0,33	0,49	0,63	0,75	1,13	0,93	0,28	0,12	0,35	0,10	0,23
	[1,24]	[1,68]	[2,41]	[2,92]	[4,02]	[3,96]	[0,90]	[0,50]	[1,40]	[0,41]	[0,75]
CMA	0,17	-0,32	-0,12	-0,27	0,38	-0,05	0,45	-0,11	-0,58	-0,05	0,22
	[0,69]	[-1,20]	[-0,53]	[-1,15]	[1,49]	[-0,22]	[1,58]	[-0,53]	[-2,59]	[-0,23]	[0,79]

(table continues)

Panel D: VW returns sorted by seasonality measured by net profits											
	1	2	3	4	5	6	7	8	9	10	L-H
CAPM											
Alpha	0,44	0,30	0,62	0,28	0,12	0,13	0,26	0,01	-0,08	0,23	0,21
	[1,61]	[1,26]	[2,75]	[1,30]	[0,56]	[0,56]	[1,25]	[0,05]	[-0,33]	[1,05]	[0,76]
Mrktf	0,73	0,54	0,68	0,60	0,59	0,61	0,63	0,52	0,72	0,63	0,10
	[14,33]	[11,81]	[15,91]	[15,07]	[14,85]	[14,29]	[16,28]	[11,88]	[16,10]	[15,46]	[1,90]
Fama-French three-factor											
Alpha	0,44	0,40	0,65	0,30	0,16	0,13	0,31	0,07	-0,06	0,33	0,12
	[1,61]	[1,66]	[2,84]	[1,38]	[0,78]	[0,57]	[1,50]	[0,30]	[-0,24]	[1,50]	[0,43]
Mrktf	0,72	0,53	0,67	0,64	0,61	0,64	0,64	0,52	0,73	0,60	0,12
	[12,19]	[10,42]	[13,66]	[13,90]	[13,48]	[13,09]	[14,49]	[10,59]	[14,11]	[12,90]	[2,05]
SMB	0,02	-0,39	-0,10	-0,20	-0,27	-0,14	-0,26	-0,28	-0,11	-0,27	0,29
	[0,15]	[-3,00]	[-0,82]	[-1,76]	[-2,39]	[-1,13]	[-2,32]	[-2,21]	[-0,82]	[-2,33]	[2,01]
HML	0,06	0,03	0,04	-0,13	-0,07	-0,13	-0,03	-0,02	-0,03	0,18	-0,12
	[0,47]	[0,27]	[0,37]	[-1,33]	[-0,72]	[-1,22]	[-0,26]	[-0,21]	[-0,22]	[1,76]	[-0,93]
Fama-French five-factor											
Alpha	0,24	0,22	0,56	0,18	0,02	0,01	0,20	-0,16	-0,33	0,27	-0,04
	[0,82]	[0,88]	[2,31]	[0,82]	[0,09]	[0,02]	[0,93]	[-0,71]	[-1,34]	[1,20]	[-0,13]
Mrktf	0,70	0,51	0,66	0,60	0,56	0,65	0,65	0,46	0,76	0,57	0,13
	[10,65]	[8,98]	[11,84]	[11,74]	[11,25]	[11,66]	[12,97]	[8,74]	[13,29]	[10,90]	[1,96]
SMB	0,03	-0,39	-0,09	-0,23	-0,30	-0,11	-0,23	-0,30	-0,02	-0,29	0,31
	[0,18]	[-2,96]	[-0,74]	[-1,95]	[-2,60]	[-0,85]	[-2,01]	[-2,42]	[-0,19]	[-2,35]	[2,06]
HML	0,46	0,46	0,25	0,23	0,41	0,06	0,14	0,64	0,28	0,40	0,06
	[2,32]	[2,69]	[1,50]	[1,53]	[2,76]	[0,37]	[0,92]	[4,05]	[1,63]	[2,54]	[0,30]
RMW	0,73	0,72	0,35	0,51	0,65	0,42	0,37	0,97	0,83	0,28	0,45
	[2,65]	[3,00]	[1,53]	[2,40]	[3,16]	[1,82]	[1,78]	[4,39]	[3,48]	[1,26]	[1,65]
CMA	-0,16	-0,18	-0,10	-0,30	-0,41	0,04	0,37	-0,50	0,23	-0,19	0,04
	[-0,63]	[-0,82]	[-0,47]	[-1,54]	[-2,18]	[0,18]	[0,39]	[-2,51]	[1,08]	[-0,98]	[0,16]

Table A2: Variables used

This table defines all the variables used during this paper.

Variable	Database	Description
AVGSEA	Eikon	The average of SEA_{qt} between years t-2 and t-3
BL	Eikon	Total debt (total long-term liabilities plus long-term debt in current liabilities) divided by total assets
BL Change	EIkon	Change in BL between quarter q and q-1
BM	Datastream	Book-to-market (book value of equity divided by market value of equity)
DISP	I/B/E/S	Dispersion in analysts' earnings forecasts is the standard deviation of earnings forecasts divided by the absolute value of the consensus mean forecast
IAQ	Eikon	Change in total assets at quarter q relative to total assets at q − 1
ICAQ	Eikon	Change in current assets at quarter q relative to current assets at q − 1

(Table continues)

INST Change	Eikon	Relative change of stocks in institutional holding of quarter q-1 to q
INVQ	Eikon	Change in inventories at quarter q relative to inventories at q − 1
ILLLIQ	Datastream	ILLQ is the quarterly average ratio of Amihud's illiquidity measure (absolute daily stock return to daily dollar trading volume.)
IVOL	Datastream	The standard deviation of CAPM residuals from month t-1
ME	Datastream	Shares outstanding times the absolute value of price in June of year t.
ML	Eikon/Datastream	Total debt (total long-term liabilities plus long-term debt in current liabilities) scaled by market value of equity(ME).
ML Change	Eikon/Datastream	Change in ML from quarter q − 1 to q .
PPEQ	Eikon	Change in net property, plan and equipment at quarter q relative to net property, plan and equipment at q − 1
SEA	Eikon	Sales in quarter q of year t scaled by the annual sales in year t. Firms are required to have nonmissing sales data for all four quarters during a particular year. When the sum of the quarterly sales does not equal the annual sales, only firm-year observations in which the sum of the quarterly sales is within 95% and 105% of the total annual sales are included
SEARANGE	Eikon	The difference between the maximum and minimum values of AVGSEA over the last four quarters
SEAVAR	Eikon	The absolute change between SEA_{qt} in year t − 3 and t − 2
STURN	Eikon	Daily volume scaled by shares outstanding, averaged over each quarter.
SEAF	Eikon/Datastream	Factor based seasonality measure formed in Fama-French convention, described in the Kenneth French website. Each month, I create two porfolios based on size(ME) and then dividing them into three based on sales seasonality (AVGSEA). I calculate value-weighted returns for each portfolio and subtract the returns of the high-sales season portfolio from the low-season portfolio for the small and big firm portfolios. Finally, I average the returns of these size-based portfolios.
SEAS	Datastream	Factor based seasonality measure formed in Fama-French convention, described in the Kenneth French website. Each month, I create two porfolios based on size(ME) and then dividing them into three based on past three year average same month return. I calculate value-weighted returns for each portfolio and subtract the returns of the high-return season portfolio from the low-return portfolio for the small and big firm portfolios. Finally, I average the returns of these size-based portfolios.

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